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Improved Copy-Move Forgery Detection Through Feature-Augmented Deep Learning Models

Anupam Chaube[1], Dr. Shweta Rai[2]
Research scholar, Department of Computer Science & Engineering, Mahakaushal University Jabalpur[1]
Associate Professor, Department of Computer Science & Engineering, Mahakaushal University Jabalpur[2]

Abstract: *Copy-move forgery represents one of the most prevalent forms of digital image manipulation, where regions from the same image are copied and pasted to conceal or duplicate objects. This study presents a comprehensive analysis of feature-enhanced deep learning algorithms for detecting copy-move forgeries in digital images. Our research investigates the effectiveness of various deep learning architectures including Convolutional Neural Networks (CNN), ResNet, and Vision Transformers (ViT) combined with traditional feature extraction methods such as Scale-Invariant Feature Transform (SIFT), Speeded Up Robust Features (SURF), and Local Binary Patterns (LBP). The experimental evaluation was conducted on multiple benchmark datasets including MICC-F2000, CoMoFoD, and COVERAGE, comprising over 15,000 images with varying levels of post-processing operations. Results demonstrate that the proposed feature-enhanced CNN-ResNet hybrid model achieves superior performance with 96.7% accuracy, 95.2% precision, and 94.8% recall, outperforming existing state-of-the-art methods by 3.2% in overall detection accuracy. The integration of multi-scale feature extraction with deep learning architectures shows significant improvement in detecting copy-move forgeries under challenging conditions including JPEG compression, noise addition, and geometric transformations. This study contributes to the advancement of digital forensics by providing robust solutions for automated forgery detection systems.*

Keywords: *Copy-move forgery, Deep learning, Feature extraction, Digital forensics, Image authentication, CNN, Computer vision.*

1. Introduction

Digital image forgery has emerged as a critical concern in the era of sophisticated image editing tools and widespread digital media consumption. The proliferation of powerful image manipulation software has made it increasingly easy for individuals to create convincing fake images, raising serious questions about digital content authenticity and trustworthiness. Among various types of image forgeries, copy-move forgery stands out as one of the most common and challenging to detect, where portions of an image are copied and pasted within the same image to hide or duplicate objects.

1.1 Problem Statement and Motivation

The detection of copy-move forgeries presents unique challenges due to the inherent similarity between the source and target regions, as they originate from the same image and share identical statistical properties. Traditional pixel-based detection methods often fail when images undergo post-processing operations such as JPEG compression, noise addition, or geometric transformations. The advent of deep learning has opened new avenues for forgery detection, offering the potential to learn complex patterns

and features automatically from data. However, the integration of traditional feature extraction methods with deep learning architectures remains an underexplored area that could significantly enhance detection performance. This research addresses the critical need for robust and accurate copy-move forgery detection systems that can operate effectively under various challenging conditions encountered in real-world scenarios.

1.2 Research Objectives and Contributions

The primary objective of this study is to develop and analyze feature-enhanced deep learning algorithms for copy-move forgery detection that can achieve high accuracy while maintaining computational efficiency. Our research contributes to the field through several key innovations: first, we propose a novel hybrid architecture that combines traditional feature extraction methods with modern deep learning models to leverage the strengths of both approaches. Second, we conduct comprehensive experimental evaluation across multiple benchmark datasets to ensure the generalizability of our findings. Third, we perform detailed analysis of the impact of various post-processing operations on detection performance, providing insights into the robustness of different algorithmic approaches. Finally, we establish new benchmarks for copy-move forgery detection performance and provide comparative analysis with existing state-of-the-art methods.

1.3 Paper Organization and Scope

This paper is structured to provide a comprehensive analysis of feature-enhanced deep learning approaches for copy-move forgery detection. The scope of our investigation encompasses the evaluation of multiple deep learning architectures, traditional feature extraction methods, and their hybrid combinations across diverse datasets representing various real-world scenarios. We focus specifically on copy-move forgeries while acknowledging the broader context of digital image forensics. The experimental methodology includes rigorous testing under different post-processing conditions to assess the practical applicability of the proposed methods. Our analysis extends beyond mere performance metrics to include computational complexity, scalability considerations, and comparative evaluation with existing approaches to provide a holistic understanding of the current state and future directions in copy-move forgery detection research.

2. Literature Survey

The field of copy-move forgery detection has evolved significantly over the past decade, with researchers exploring various approaches ranging from traditional block-based methods to sophisticated deep learning architectures. Early works in this domain primarily relied on block-matching algorithms and keypoint-based methods, which, while effective in controlled conditions, showed limitations when dealing with post-processed images or complex transformations. Block-based approaches, pioneered by Fridrich et al., segment images into overlapping blocks and compare their similarity using various distance metrics. These methods demonstrated reasonable performance on uncompressed images but struggled with JPEG compression and geometric transformations. Subsequent research focused on keypoint-based methods utilizing features like SIFT and SURF, which showed improved robustness to geometric transformations but remained vulnerable to noise and compression artifacts. The introduction of local feature descriptors such as LBP and histogram-based methods provided better texture analysis capabilities but still faced challenges in distinguishing between genuine similarities and copy-move operations.

The emergence of deep learning in computer vision has revolutionized forgery detection approaches. Convolutional Neural Networks have shown remarkable success in learning hierarchical features automatically, eliminating the need for manual feature engineering. Recent studies have explored various CNN architectures, including ResNet, DenseNet, and EfficientNet, for forgery detection tasks. Vision Transformers have also gained attention for their ability to capture long-range dependencies and global context information. However, most existing deep learning approaches focus solely on end-to-end learning without leveraging the rich knowledge accumulated in traditional feature extraction methods. The integration of classical features with deep learning architectures represents a promising research direction that has received limited attention in the literature. Contemporary research has also emphasized the importance of comprehensive evaluation across diverse datasets and challenging conditions. Studies have highlighted the significant performance variations across different datasets and the need for robust evaluation protocols. The development of sophisticated post-processing attacks and the increasing availability of powerful editing tools have necessitated more robust detection methods. Multi-scale analysis and ensemble approaches have emerged as effective strategies for improving detection accuracy and robustness. Recent works

have also explored attention mechanisms and transfer learning techniques to enhance the discriminative power of deep learning models for forgery detection applications.

3. Methodology

The proposed methodology integrates traditional feature extraction techniques with modern deep learning architectures to create a robust copy-move forgery detection system. Our approach consists of three main components: feature extraction and enhancement, deep learning model architecture, and fusion strategy. The feature extraction module employs multiple traditional methods including SIFT for keypoint detection, SURF for robust feature description, and LBP for texture analysis. These features are extracted at multiple scales to capture both local and global image characteristics. The deep learning component utilizes a hybrid CNN-ResNet architecture that combines the feature learning capabilities of convolutional layers with the depth and skip connections of ResNet blocks. The feature enhancement process begins with preprocessing the input images to normalize illumination and reduce noise effects. Multiple feature extractors operate in parallel to generate complementary representations of the image content. SIFT features capture distinctive keypoints that are invariant to scale and rotation, while SURF provides faster computation with comparable robustness. LBP features encode local texture patterns that are particularly effective for detecting subtle manipulations. These traditional features are then transformed into deep feature representations through learned embedding layers that adapt the traditional features to the deep learning framework. The enhanced features are concatenated with the deep CNN features to form a comprehensive representation that leverages both hand-crafted and learned features. The proposed deep learning architecture consists of a feature extraction backbone based on ResNet-50, followed by custom layers designed specifically for forgery detection. The backbone network processes input images through multiple convolutional blocks with skip connections, enabling the learning of complex hierarchical features while avoiding gradient vanishing problems. The final layers include spatial attention mechanisms that focus on potentially forged regions and global average pooling to reduce computational complexity. The fusion strategy combines traditional and deep features through learnable weighted concatenation, allowing the model to automatically determine the optimal contribution of each feature type. The training process employs transfer learning from ImageNet pretrained weights, followed by fine-tuning on forgery detection datasets using carefully designed loss functions that emphasize both detection accuracy and localization precision.

4. Data Collection and Analysis

The experimental evaluation was conducted using multiple benchmark datasets to ensure comprehensive assessment of the proposed methods. The primary datasets include MICC-F2000 containing 2,000 images with copy-move forgeries, CoMoFoD with 512 forged images under various transformations, COVERAGE dataset with 100 high-resolution images, and CASIA v2.0 containing 5,123 authentic and 5,124 tampered images. Additionally, we created a custom dataset of 2,500 images with controlled copy-move operations to evaluate specific algorithmic components. The datasets were carefully balanced to include various image categories, resolutions, and post-processing operations including JPEG compression, Gaussian noise, rotation, scaling, and combination attacks.

Table 1: Dataset Characteristics and Distribution

Dataset	Total Images	Forged Images	Authentic Images	Average Resolution	Post-processing Types
MICC-F2000	2000	1300	700	2048×1536	JPEG, Rotation, Scaling
CoMoFoD	1024	512	512	512×512	Rotation, Scaling, Noise
COVERAGE	200	100	100	1920×1080	JPEG, Blur, Noise
CASIA v2.0	10247	5124	5123	Variable	Multiple Operations
Custom Dataset	2500	1500	1000	1024×1024	Controlled Operations

Table 2: Performance Comparison of Different Algorithms

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Processing Time (ms)
SIFT-based	78.3	76.2	79.1	77.6	145
SURF-based	81.7	80.4	82.3	81.3	98
CNN-basic	89.2	87.8	90.1	88.9	67
ResNet-50	92.5	91.3	93.2	92.2	89
Proposed Hybrid	96.7	95.2	94.8	95.0	112

Table 3: Robustness Analysis Under Different Post-processing Operations

Post-processing	Traditional Methods (%)	Deep Learning (%)	Proposed Method (%)
JPEG Q=70	65.4	87.2	91.8
JPEG Q=50	58.9	82.1	88.4
Gaussian Noise σ=2	62.3	85.6	89.7
Rotation 5°	71.2	88.9	93.2
Scaling 0.9x	69.8	87.4	92.1
Combined Attacks	54.7	79.3	86.5

Table 4: Feature Importance Analysis

Feature Type	Contribution Weight	Detection Accuracy	Computational Cost
SIFT Features	0.23	78.3%	Low
SURF Features	0.19	81.7%	Medium
LBP Features	0.16	74.9%	Low
CNN Features	0.42	89.2%	High
Combined Features	1.00	96.7%	Medium-High

Table 5: Comparative Analysis with State-of-the-art Methods

Reference Method	Year	Accuracy (%)	Dataset Used	Key Innovation
BusterNet [15]	2019	89.4	CASIA	Two-branch CNN
ManTra-Net [18]	2020	91.2	Multiple	Self-attention mechanism
SPAN [22]	2021	93.5	CoMoFoD	Spatial attention
CAT-Net [25]	2022	94.8	COVERAGE	Cross-attention transformer
Proposed Method	2024	96.7	Multiple	Feature-enhanced hybrid

The data analysis reveals several key insights regarding the effectiveness of different approaches for copy-move forgery detection. Traditional methods show reasonable performance on unprocessed images but suffer significant degradation under post-processing operations. Deep learning methods demonstrate superior robustness to various attacks but may miss subtle manipulations that traditional features can detect. The proposed hybrid approach achieves the best overall performance by combining the strengths of both paradigms. Feature importance analysis indicates that CNN features contribute most significantly to detection accuracy, while traditional features provide complementary information that improves robustness. The processing time analysis shows that while the hybrid method requires more computation than individual approaches, the performance gain justifies the additional complexity for critical applications requiring high accuracy.

5. Discussion

The experimental results demonstrate the effectiveness of integrating traditional feature extraction methods with deep learning architectures for copy-move forgery detection. The proposed hybrid approach achieves superior performance compared to individual methods, validating the hypothesis that combining hand-crafted and learned features can enhance detection capabilities. The 96.7% accuracy achieved by our method represents a significant improvement over existing approaches, particularly in challenging scenarios involving post-processing operations. The critical analysis of the results reveals several important findings. First, the robustness analysis shows that traditional methods struggle significantly with compressed and noisy images, while deep learning approaches maintain better performance but still show degradation. The proposed hybrid method demonstrates the most consistent performance across different attack scenarios, suggesting that the combination of features provides complementary information that enhances overall robustness. The feature importance analysis indicates that while CNN features dominate the decision-making process, traditional features contribute meaningfully to edge cases where deep learning alone may fail. Comparison with recent state-of-the-art methods shows that our approach outperforms existing techniques across multiple evaluation metrics. The improvement is particularly notable in precision, where the careful integration of multiple feature types helps reduce false positive rates. The BusterNet approach, while innovative in its two-branch architecture, lacks the feature diversity provided by our hybrid method. ManTra-Net's self-attention mechanism shows promise but operates solely in the deep learning domain without leveraging traditional computer vision knowledge. SPAN's spatial attention approach addresses localization challenges but does not achieve the same level of accuracy as our method. CAT-Net's cross-attention transformer represents the current state-of-the-art but focuses primarily on transformer architectures without exploring the integration of traditional features. The computational analysis reveals trade-offs between accuracy and efficiency. While the proposed method requires more processing time than individual approaches, the improvement in detection accuracy justifies the additional computational cost for applications where accuracy is critical. The processing time of 112ms per image remains acceptable for real-time applications, particularly considering the complexity of the forgery

detection task. The scalability analysis suggests that the method can be optimized further through architectural improvements and hardware acceleration. Future work should focus on developing more efficient fusion strategies and exploring lightweight architectures that maintain high accuracy while reducing computational requirements. The integration of attention mechanisms specifically designed for feature fusion could further improve performance while maintaining computational efficiency.

6. Conclusion

This study presents a comprehensive analysis of feature-enhanced deep learning algorithms for copy-move forgery detection, demonstrating significant improvements over existing methods through the strategic integration of traditional and modern approaches. The proposed hybrid architecture achieves 96.7% accuracy, representing a 3.2% improvement over current state-of-the-art methods while maintaining robustness across various post-processing operations. The experimental evaluation across multiple benchmark datasets validates the generalizability and practical applicability of the approach. The key contributions of this research include the development of a novel feature fusion strategy that effectively combines SIFT, SURF, and LBP features with deep CNN representations, comprehensive evaluation demonstrating superior performance under challenging conditions, and detailed analysis of feature importance and computational trade-offs. The results indicate that the integration of traditional computer vision knowledge with deep learning capabilities provides complementary strengths that enhance overall detection performance. Future research directions include exploring more sophisticated attention mechanisms for feature fusion, investigating the application of transformer architectures in the hybrid framework, and developing real-time optimization strategies for deployment in practical applications. The findings of this study contribute to advancing the field of digital forensics and provide a foundation for developing more robust and accurate image authentication systems in an increasingly digital world.

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